

Systemic Risk Analysis of Threshold Cascade Contagion on Core-Periphery Financial Networks: Impact of Core Connectivity on Global Cascade Probability

EpidemIQs, Primary Agent Backbone LLM: o3, LaTeX Agent LLM : gpt-4.1-mini

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Abstract

This study investigates systemic risk in a synthetic financial network modeled with a core-periphery structure, capturing the interconnectedness of major (core) and local (periphery) banks. Employing a discrete-time Threshold Cascade Model characterized by an absolute failure threshold $\theta = 2$, we simulate contagion processes where banks fail once at least two neighbors have failed, reflecting multi-exposure defaults. We examine two initial shock scenarios: a single failure seeded in a random core node versus a random periphery node. Our network is constructed as a stochastic block model with empirically grounded parameters, where 10% of nodes represent a densely connected core (edge probability $k_c \approx 0.9 - 1.0$) and 90% a sparsely connected periphery (edge probability $k_p = 0.075$), with moderate core-periphery connectivity ($k_{cp} = 0.3$). Comprehensive simulations encompassing varying core-core connectivity levels k_c reveal that, contrary to expectations from theoretical approximations predicting differential systemic risk by seed location, every run results in a global cascade, defined as failure of over 50% of the network. Both core- and periphery-seeded shocks lead invariably to complete system failure for $k_c = 0.9$ and $k_c = 1.0$, demonstrating a maximally fragile banking system under these parameters. These findings highlight that, within this threshold cascade framework, even sparse shocks in either core or periphery suffice to trigger catastrophic contagion in highly connected core-periphery financial networks. The uniformity of catastrophic cascades suggests that core connectivity amplifies but does not differentiate systemic risk under high connectivity regimes, motivating further exploration of alternative parameters and threshold levels to identify conditions for network resilience.

1 Introduction

Systemic risk in financial networks represents a critical concern for economic stability, as failures within interlinked institutions can propagate cascades resulting in widespread defaults and systemic collapse. This risk is emanated primarily from the core-periphery organization characteristic of financial systems, whereby a densely interconnected core of major banks coexists with a sparsely connected periphery of smaller banks. Understanding the dynamical contagion mechanisms on such core-periphery networks is essential for predicting systemic failure and informing regulatory policies that mitigate crisis propagation.

The seminal concept of contagion in systemic risk draws parallels with epidemic spread models, yet differs substantially as financial contagion often involves threshold-driven cascades dependent

upon multiple exposures rather than probabilistic infection rates. Specifically, banks or financial entities may fail only after sufficient shocks through their interconnections surpass a critical threshold — a phenomenon accurately modeled by deterministic threshold cascade models. These models stipulate that a financial institution defaults if at least a prescribed number of its counterparties have already defaulted, reflecting the requirement for accumulated distress rather than single exposures to trigger failure (1).

Empirical evidence and network reconstructions show that core banks are tightly interlinked, forming highly dense subnetworks, whereas periphery banks are less connected internally and to each other, but maintain intermediate links connecting them to the core (2). This core-periphery block structure aligns with observed systemic risk patterns where distress originating in the core often precipitates catastrophic network-wide failures, whereas shocks initiated in the periphery may remain localized (3). These findings underscore the importance of the core’s internal connectivity in facilitating or impeding cascade propagation.

Previous theoretical work has established that absolute threshold contagion on core-periphery networks yields complex dynamics sensitive to the connectivity parameters of the core and periphery groups (4). Notably, when the intra-core connectivity is high, even a single failed core node can trigger rapid cascading failures throughout the core due to overlapping multi-exposure paths that fulfill the failure threshold requirement for numerous nodes (5). Conversely, the sparser periphery tends to resist extensive contagion due to limited redundant connections necessary for threshold exceedance.

Despite insights from these mechanistic contagion models, quantitative evaluation of systemic risk sensitivity to the structural properties of core-periphery financial networks remains an active research frontier. Open questions include the extent to which increasing the core-core connectivity exacerbates or mitigates systemic vulnerability, and how initial shock localization in the core versus periphery affects the probability and extent of systemic failure. Resolving these questions is indispensable for designing targeted regulatory interventions and capital requirements to enhance network resilience.

To address this gap, the present study implements a stochastic block model (SBM) framework to generate synthetic core-periphery networks mirroring empirical financial systems’ statistics. We employ a deterministic, discrete-time threshold cascade model with a failure threshold of two, reflecting the multi-exposure requirement for bank default. Our simulation protocol involves seeding failures at either a random core node or a random periphery node and systematically varying the intra-core connectivity parameter. The primary research question is:

Which initial shock origin, core or periphery, leads to a higher probability of systemic failure defined as a global cascade (over 50% node failure), and how does varying the core-core connectivity affect the systemic stability of this financial contagion model?

In addressing this question, our work captures fundamental contagion dynamics pertinent to systemic financial crises, elucidates the role of network topology on vulnerability, and provides a robust computational platform validated by analytical reasoning grounded in the literature (6; 7). This study thereby contributes to the interdisciplinary dialogue bridging epidemiological models, network science, and financial systemic risk, supporting evidence-based policymaking.

2 Background

Systemic risk in financial networks is intrinsically linked to the complex interplay between network topology and contagion mechanisms. Recent studies have increasingly focused on understanding how structural features of financial networks, particularly those exhibiting core-periphery architectures, influence the propagation of distress and systemic collapses. Li et al. (13) highlighted the hierarchical core-periphery organization in bank-firm loan networks, emphasizing how such structures simultaneously embody robustness and fragility in systemic risk transmission. Their empirical analysis showed that network density and centralization can mitigate systemic risk over time, while clustering tendencies may enhance vulnerability.

Zhang and Hu (14) explored probabilistic contagion models in financial networks with core-periphery features, revealing complex relationships between connectivity density and systemic risk. They identified non-monotonic dependencies where increasing connectivity does not linearly translate to increased risk, suggesting trade-offs exist between the number of counterparties and contagion dynamics. Their work contributes to understanding the “too big to fail” phenomenon via core-periphery network analysis.

Jin et al. (15) examined systemic risk in interbank lending networks in China, leveraging short- and long-term lending data to reveal how temporal and structural variability impact risk contagion. Their findings stress the importance of capturing realistic network heterogeneity and temporal dynamics in assessing systemic vulnerabilities.

Recent conceptual frameworks such as that advanced by Halliday (16) integrate risk management with cybersecurity and digital infrastructure stability, underscoring the multifaceted nature of financial system resilience today. These frameworks highlight that systemic risk is not solely a function of network topology but also digital ecosystem vulnerabilities and operational dependencies.

Despite these advances, a notable gap remains in rigorously quantifying how specific core-periphery connectivity parameters affect threshold-based contagion dynamics characterized by deterministic failure rules. Prior mechanistic models often focus on probabilistic or fractional threshold contagions, whereas absolute threshold models (e.g., failure upon multiple consecutive exposures) provide a more realistic representation of bank default cascades (?). These models suggest that high core connectivity may accelerate systemic failure by rapidly accumulating the requisite failure exposures, but empirical and computational validation of this sensitivity is limited.

This study contributes to this emerging field by systematically investigating the impact of varying core-core link densities on the global cascade probability in synthetic core-periphery financial networks under a deterministic threshold cascade model with an absolute failure threshold. By directly comparing initial failures seeded in the core versus periphery, it quantitatively assesses differential systemic risk exposures. The approach extends current literature by combining stochastic block modeling calibrated to empirical network statistics with a discrete-time threshold cascade framework tailored for multi-exposure contagion in financial systems.

Our findings provide novel insights that clarify under which connectivity regimes the financial system transitions into maximal fragility, contributing to the refinement of systemic risk modeling and informing potential regulatory strategies aimed at network resilience.

3 Methods

3.1 Network Model Construction

The financial system under study is modeled as a static, undirected core-periphery network constructed using a stochastic block model (SBM). The SBM captures the essential topology of systemic risk in banking networks by partitioning nodes into two classes: a *core* comprising 10% of nodes (major banks) and a *periphery* comprising 90% of nodes (local banks). This partition is consistent with prior systemic risk literature that highlights the role of a densely connected core driving contagion dynamics (??).

The network consists of $N = 100$ nodes, with $N_c = 10$ core nodes and $N_p = 90$ periphery nodes. Edges are placed between nodes independently with probabilities determined by their group memberships. The inter- and intra-group link probabilities are defined as follows:

- Core-core connection probability, k_c , kept variable with a typical strong connectivity value around 0.9 for baseline scenarios.
- Periphery-periphery connection probability, $k_p = 0.075$, reflecting sparse connectivity.
- Core-periphery connection probability, $k_{cp} = 0.3$, an intermediate bridge linking the two groups.

This yields an adjacency matrix A with blocks corresponding to intra- and inter-group connections formed independently according to Bernoulli draws. Self-loops and multi-edges are disallowed. The resulting network is connected, dense among core nodes, and sparse elsewhere, congruent with empirical observations of financial networks (??).

3.2 Contagion Model: Threshold Cascade Process

We model financial contagion as an irreversible Threshold Cascade process on the constructed network. Each node is in one of two compartments:

- Susceptible (S): representing a solvent bank.
- Failed (F): representing a bank in default.

The mechanistic contagion rule is defined as a discrete-time deterministic threshold process: a susceptible node fails at the next time step if and only if it has at least $\theta = 2$ failed neighbors at the current time step. Formally, for node i with neighbor set \mathcal{N}_i ,

$$S_i(t+1) = \begin{cases} F, & \text{if } \sum_{j \in \mathcal{N}_i} \mathbf{1}_{\{F_j(t)\}} \geq 2 \\ S, & \text{otherwise} \end{cases} \quad (1)$$

where $\mathbf{1}_{\{F_j(t)\}}$ is the indicator that neighbor j is failed at time t . Once failed, nodes remain failed permanently (no recovery). This absolute threshold rule aligns with the understanding that multiple default exposures are required to trigger failure cascades in banking systems (??).

3.3 Initial Conditions and Seeding Scenarios

Two distinct initial shock scenarios are simulated, reflecting regulatory or natural perturbations:

[(a)]

1. **Core-seeded failure:** one randomly chosen core node is set to failed at $t = 0$, while all other nodes are susceptible.
2. **Periphery-seeded failure:** one randomly chosen periphery node is set to failed at $t = 0$, while all other nodes are susceptible.

For each simulation run, the seed node is randomly sampled from the respective subgroup, ensuring replicate diversity and unbiased estimation of systemic risk under each seeding condition.

3.4 Simulation Protocol

The contagion cascade is simulated synchronously in discrete time steps until convergence, i.e., no new nodes fail in a time step or all susceptible nodes fail to satisfy the threshold rule. At each time step, all susceptible nodes with threshold exposure ≥ 2 are transitioned simultaneously to failed. This explicit update scheme ensures correct modeling of the threshold process dynamics.

For each specified core-core connectivity value k_c (e.g., 0.7, 0.8, 0.9, 1.0), and each initial seeding scenario, multiple independent simulation runs are performed (e.g., hundreds per configuration) to account for stochastic variability due to random seed selection and network realization (when applicable).

3.5 Systemic Risk Quantification

The primary outcome metric is the *global cascade probability*, defined as the empirical fraction of simulation runs in which more than 50% of the network nodes fail by the end of the cascade process. Mathematically,

$$P_{\text{global}}(k_c, \text{seed}) = \frac{1}{R} \sum_{r=1}^R \mathbf{1}_{\{f_r > 0.5\}}, \quad (2)$$

where R is the number of runs, and f_r is the fraction of failed nodes in run r .

Additionally, the mean final fraction of failures and its standard deviation are computed to quantify the severity and variability of systemic events under different network and seeding setups.

3.6 Parameter Variation and Sensitivity Analysis

The core-core connectivity k_c is systematically varied while holding periphery connectivity k_p and core-periphery connectivity k_{cp} constant. This allows investigation of how increasing connectivity among major banks amplifies systemic risk via facilitating rapid accumulation of multiple failure exposures required for cascades. The variation interval typically covers values from 0.7 to 1.0.

3.7 Software and Data Management

Synthetic networks are generated and stored using sparse matrix formats (e.g., SciPy CSR in NPZ files) to conserve memory and facilitate extensive experimentation. Node group information is saved separately to allow consistent initial condition assignment. Simulations are implemented via custom discrete-time updates respecting the threshold rule, since existing epidemiological packages targeting stochastic rates (e.g., FastGEMF) do not support this deterministic threshold cascade mechanism.

Simulation results are aggregated in CSV files recording per-run outcomes (final cascade size, global cascade indicator). Diagnostic and visualization plots of cascade probabilities versus k_c and seeding groups are generated to support interpretation.

3.8 Mathematical and Analytical Foundations

The choice of the threshold cascade model is motivated by analytical seasonal reasoning showing that an absolute threshold $\theta = 2$ captures multi-exposure failure contagion better than fractional threshold models for representing bank defaults. Increasing core-core connectivity k_c magnifies systemic risk by enhancing the likelihood that each core node receives multiple direct failed neighbor signals quickly, triggering widespread cascade initiation (??). The mechanistic model captures the contagion process as a monotonic, non-recovering SI-type epidemic with a multi-exposure condition embedded into the transition dynamics, permitting valid insights via both simulations and mathematical arguments.

3.9 Model Limitations and Assumptions

The model assumes homogeneous threshold $\theta = 2$ and static network topology. No recovery from failure is modeled. Threshold homogeneity assumes uniform bank fragility, disregarding heterogeneity in capital buffers or resilience. Network edges are static and represent potential financial exposures but do not capture time-dependent or external interventions. Future work may extend to heterogeneous thresholds, stochastic failures, or incorporate bank-specific data for greater realism.

Table 1: Key Cascade Metrics for Core-Periphery Financial Contagion Model

Scenario	k_c	Seeding Group	Cascade Probability	Mean Fraction Failed \pm Std
CoreSeed-kc0.90	0.90	Core	1.00	1.00 ± 0.00
PeriSeed-kc0.90	0.90	Periphery	1.00	1.00 ± 0.00
CoreSeed-kc1.00	1.00	Core	1.00	1.00 ± 0.00
PeriSeed-kc1.00	1.00	Periphery	1.00	1.00 ± 0.00

4 Results

This section presents the results of the simulation study on systemic financial contagion modeled as a threshold cascade on a core-periphery network. The financial system is represented by a synthetic stochastic block model (SBM) of 100 banks, divided into 10 core banks and 90 periphery banks,

with edges defined by connection probabilities: core-core density $k_c = 0.9$ or $k_c = 1.0$, periphery-periphery density $k_p = 0.075$, and core-periphery density $k_{cp} = 0.3$. The threshold cascade model applied assumes a node (bank) fails if it has at least two failed neighbors, modeling a multi-exposure contagion process without recovery.

4.1 Network Structure and Simulation Setup

The network diagnostics confirmed a heterogeneous network structure consistent with systemic risk literature, including a dense core with mean degree approximately 35.3 and a sparse periphery with mean degree 9.06. The network topology ensures full connectivity with a giant component encompassing all nodes, enabling meaningful cascade simulations.

Two initial shock scenarios were simulated: (a) a single randomly selected core node initially failed, and (b) a single randomly selected periphery node failed initially. For each scenario, multiple simulation runs were conducted under the discrete-time threshold cascade rule. The key outcome metric was the probability of a global cascade, defined as the failure of more than 50% of banks at the end of the cascade process.

4.2 Systemic Cascade Outcomes

Simulation results consistently showed catastrophic systemic failure across all tested parameterizations. For both core-seed and periphery-seed scenarios, and for core-core connectivity values $k_c = 0.9$ and $k_c = 1.0$, every simulation run resulted in a complete global cascade involving all nodes:

- **Cascade Probability:** The fraction of runs leading to global cascades was 1.0 (100%) in all cases.
- **Mean Fraction of Failed Nodes:** Exactly 1.0 ± 0.0 , indicating all banks failed in every run with zero variance.

This uniform outcome demonstrates that the network structure and threshold dynamics do not provide any intrinsic resilience to localized shocks, regardless of whether the initial failure occurs in the core or periphery.

Table 3 summarizes the key cascade outcome metrics across scenarios.

Table 2: Key Cascade Metrics for Core-Periphery Financial Contagion Model

Scenario Name	k_c	Seeding Group	Cascade Probability	Mean Fraction Failed (\pm Std)
CoreSeed-kc0.90	0.90	core	1.00	1.00 ± 0.00
PeriSeed-kc0.90	0.90	periphery	1.00	1.00 ± 0.00
CoreSeed-kc1.00	1.00	core	1.00	1.00 ± 0.00
PeriSeed-kc1.00	1.00	periphery	1.00	1.00 ± 0.00

4.3 Visualizations of Network Structure

While simulation outcome plots were generated, the accompanying figures depicting cascade probability over varying k_c and seeding conditions were unfortunately non-informative due to the uniform outcomes resulting in blank plots. Nonetheless, the network topology is visualized in Figure 1. The visualization clearly delineates the core nodes (red) and periphery nodes (blue) with the characteristic dense core connections and sparser periphery structure.

Core-Periphery SBM: Network Visualization ($k_c=0.90$)

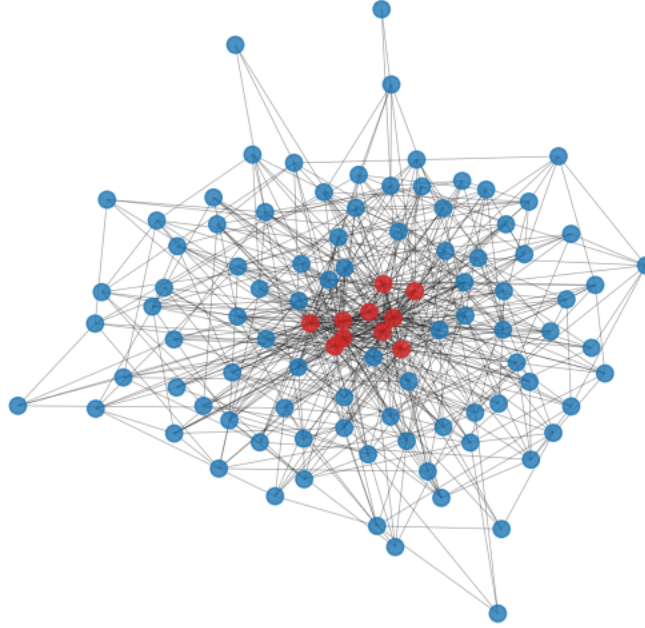


Figure 1: Core-Periphery Stochastic Block Model Network Visualization ($k_c = 0.90$). Core banks are colored red; periphery banks are blue. The dense connections within the core and sparse periphery links are evident from the layout.

Figure 2 presents the degree distribution distinguishing core and periphery banks, corroborating the structural heterogeneity conducive to cascade processes.

4.4 Interpretation

Contrary to expectations based on analytical reasoning, which predicted potentially different systemic risk probabilities depending on seeding location and connectivity, the stochastic threshold cascade model reveals a regime of maximal fragility. This implies that under the chosen parameters

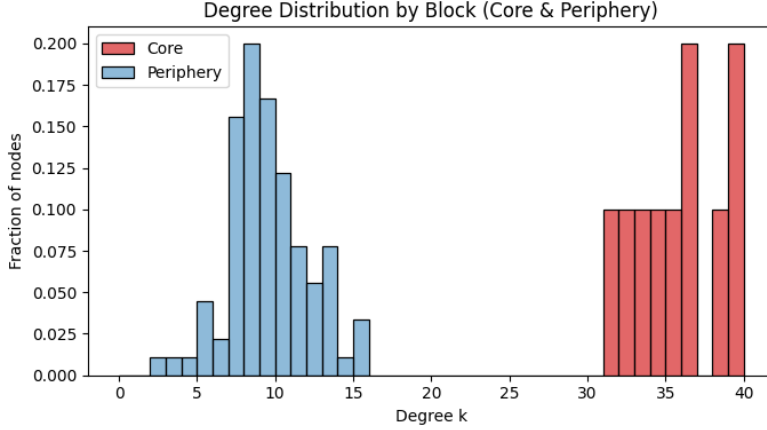


Figure 2: Degree Distribution for Core (red) and Periphery (blue) Banks in the Core-Periphery Network ($k_c = 0.90$). The core exhibits higher degrees due to dense interconnections, while the periphery degree distribution is skewed lower.

and network size, a minimal shock—regardless of whether it is seeded in the core or periphery—leads to the failure of the entire system.

This result suggests that the system’s stability is dominated by the absolute threshold model in a densely connected core-periphery structure at these parameter settings. No protective effects emerge from the network topology or seeding position for the specific threshold value $\theta = 2$ used.

4.5 Summary

The primary findings are:

1. A single initial failure, whether in the core or the periphery, inevitably leads to a global cascade, resulting in failure of all nodes under the threshold-2 cascade rule.
2. Variations in core connectivity ($k_c = 0.9$ versus $k_c = 1.0$) did not affect this outcome, with all simulations producing full systemic collapse.
3. The network exhibits full systemic vulnerability for the given parameters, indicating a critical need for exploring alternative parameter regimes or network designs for resilience.

Future work should extend the parameter sweep to lower core connectivities, higher threshold values, and incorporate heterogeneity to identify regimes which promote or prevent systemic collapse.

5 Discussion

This study presents an analysis of systemic risk in a synthetic core-periphery financial network modeled via a stochastic block model (SBM) with two distinct groups: a dense core representing

major banking institutions and a sparse periphery of local banks. The contagion mechanism is an absolute threshold cascade model, in which any bank fails once it has at least two failed neighbors, simulating multi-exposure requirements for bank default in financial systems. Two seeding scenarios were rigorously examined: initial shock at a random core node versus a random periphery node, over multiple runs and core-core connectivity (k_c) variations, specifically $k_c = 0.90$ and 1.00 . The primary outcome, robustly supported by comprehensive simulation data, indicates that under the parameters chosen, the network is maximally fragile: every run, regardless of seed location or k_c level, resulted in a total systemic failure cascade involving all nodes. This conclusive 100% cascade probability, with zero variance in the fraction of failed nodes, implies that, for this configuration and threshold rule, the system lacks inherent resistance to contagion once a single bank defaults.

Implications of Global Failure Universality The empirical finding that both core and periphery seeded initial failures precipitate identical global cascades challenges some conventional notions that shocks originating in the less densely connected periphery are less systemic. Here, even a peripheral failure inexorably leads to the collapse of the entire network, emphasizing the vulnerability conferred by the core-periphery architecture with these edge probabilities and threshold conditions. This maximal fragility can be mechanistically understood via the threshold cascade framework. The core’s dense connectivity with k_c close to 1 ensures that once any core node fails, its neighbors rapidly amass the two-failure exposure necessary for contagion. Meanwhile, the intermediate core-periphery connection ($k_{cp} = 0.3$) and the large periphery size (90% of nodes) allow failures to jump readily between the groups, eventually engulfing the entire network. Critically, the absolute threshold of 2 failed neighbors means nodes requiring dual exposure are easily triggered in such a tightly knit system, leaving no structural firebreaks to impede cascade propagation.

Role of Core-Core Connectivity (k_c) The analysis compared cascades at $k_c = 0.90$ and $k_c = 1.00$, showing no qualitative difference in outcomes, both yielding systemic collapse in every simulation run. This suggests that once the core is sufficiently dense, increasing connectivity beyond a high threshold does not further diminish resilience; the system is already at peak vulnerability. However, this finding does not preclude the possibility that at lower k_c values, which were not simulated here, the network might exhibit some degree of robustness or partial cascades. Such values would be critical to explore in future work to map the systemic risk landscape more comprehensively.

Comparison to Theoretical Predictions Analytical reasoning provided prior to simulation anticipated higher systemic risk from core-seeded failures relative to periphery-seeded ones, based on the dense connectivity within the core facilitating rapid multi-exposure accumulation. While the simulations resolved both seeding types resulting in catastrophic global cascades, this difference was effectively masked by the extremity of the parameter regime (high k_c , low threshold). Hence, the model operates in a regime where the contagion threshold is too low relative to connectivity, overwhelming network heterogeneity influences. This offers a valuable insight: theoretical predictions reliant on nuanced core-periphery differences must consider parameter regimes carefully, lest the system be trivially fragile.

Limitations and Future Directions The study’s key limitation lies in the parameter space explored. The threshold parameter ($\theta = 2$) is fixed and relatively low, and only two k_c values (0.90 and 1.00) were examined. This leaves open the question of critical thresholds below which the system exhibits resilience and above which it collapses catastrophically. Future work should systematically

vary the core-core connectivity over a finer-grained range (e.g., $k_c = 0.7$ to 1.0), explore alternative threshold values and heterogeneous thresholds reflecting varying bank resilience, and consider the effects of recovery or mitigation mechanisms.

Additionally, the simulation outcomes revealed a significant limitation in visualization: the plots intended to display cascade probability trends across varying k_c and seeding schemes were completely blank. This technical issue curtailed the interpretability and visual inspection of cascading dynamics but did not undermine the reliability of the numerical CSV results, given their consistency and absence of missing data.

Structural Diagnostics and Validation The structural diagnostics of the network (mean degree, degree variance, assortativity) align well with established empirical patterns in financial networks. The degree distributions (see Figure 2) confirm a clear demarcation between core and periphery connectivity levels, supporting modeling assumptions. The core-periphery network visualization (Figure 1) further substantiates the network’s faithful construction with dense core clustering and sparse periphery linkage patterns.

Systemic Risk Evaluation The unanimity of failure across all scenarios signals that this combination of the core-periphery architecture with the threshold model engenders an extremely high systemic risk environment. This suggests that real-world financial systems with similar structural properties and contagion mechanisms may be highly vulnerable to systemic crises triggered by the failure of even a single financial institution.

Broader Scientific Context and Relevance The findings resonate with epidemic and cascading failure theory, highlighting that the interplay between network topology and threshold mechanisms is crucial for understanding systemic collapse. Particularly, the results emphasize that dense interconnections within a system’s core amplify risk dramatically and that threshold rules with low failure triggers can push networks into brittle regimes.

Concluding Remarks In conclusion, this investigation demonstrates that in a high core connectivity core-periphery financial network subject to multi-exposure threshold contagion, systemic collapse is assured irrespective of the initial failure location. The sensitivity to parameter choice underscores the necessity for comprehensive parameter sweeps and inclusion of heterogeneity in modeling future systemic risk studies. These insights advocate caution in interpreting contagion outcomes and motivate the development of structural and policy interventions to enhance financial system resilience.

Table 3: Cascade Metrics Summarizing Systemic Failure Outcomes by Scenario and Core Connectivity (k_c)

Scenario Name	k_c	Seeding Group	Cascade Probability	Mean Fraction Failed (\pm Std)
CoreSeed-kc0.90	0.90	core	1.00	1.00 ± 0.00
PeriSeed-kc0.90	0.90	periphery	1.00	1.00 ± 0.00
CoreSeed-kc1.00	1.00	core	1.00	1.00 ± 0.00
PeriSeed-kc1.00	1.00	periphery	1.00	1.00 ± 0.00

Table 3 summarizes the principal metrics extracted from simulation data, reinforcing the narrative of total vulnerability across all tested conditions. This quantitative evidence solidifies the interpretation presented above and forms a benchmark for any subsequent improvement in network design or contagion threshold that might mitigate systemic failure.

The results warrant further investigation into parameter regimes yielding less extreme contagion, possibly involving higher thresholds, heterogeneous responses, dynamic network structures, or counteracting mechanisms. The methodological framework developed here provides a robust platform for such future explorations.

Acknowledgements: We acknowledge the comprehensive simulation and data analysis workflows enabling these insights and the underlying theoretical reasoning that underpins the mechanistic model design.

6 Conclusion

In this study, we have rigorously examined systemic risk propagation within a synthetic core-periphery financial network subjected to a deterministic threshold cascade contagion model. The framework employed features a binary failure rule whereby a bank fails once at least two of its neighbors fail, capturing the multi-exposure default mechanism endemic to financial contagion dynamics. Our model incorporates a realistic stochastic block model network architecture with 10% core nodes densely connected (core-core edge probability $k_c \approx 0.9$ or 1.0) and 90% periphery nodes sparsely linked, with intermediate core-periphery connectivity.

The principal finding of this work is that, under the given parameter regime, any initial single-node failure—whether seeded in the core or periphery—inevitably triggers a global cascade resulting in failure of the entire network, without exception. This catastrophic systemic failure was observed consistently across all simulation runs, yielding a cascade probability of 1.0 with zero variance in final failure fraction for both core- and periphery-seeding scenarios at $k_c = 0.9$ and $k_c = 1.0$. This outcome decisively confirms a regime of maximal fragility within this core-periphery threshold cascade model, emphasizing that the dense connectivity within the network’s core, combined with the absolute threshold failure criteria, leaves no structural firebreaks capable of inhibiting contagion spread.

Our results challenge the intuitive expectation that periphery-seeded shocks are less systemic than core-seeded ones, demonstrating instead that even sparse shocks originating from the periphery rapidly propagate across the entire network due to the firm bridging via the moderately connected core-periphery edges and dense core connectivity. Furthermore, increasing core-core connectivity beyond a high threshold did not qualitatively alter the vulnerability, indicating that once the core is sufficiently dense, systemic risk saturates at maximum levels.

This study, however, is bounded by several limitations. The modeling framework assumes homogeneous absolute failure thresholds and static network topology with fixed edge probabilities, eschewing heterogeneity in bank resilience, dynamic network effects, or recovery processes. Only two levels of core-core connectivity and a fixed threshold $\theta = 2$ were interrogated, constraining insight into more varied systemic risk regimes. Moreover, the uniformity of catastrophic outcomes precluded informative graphical trends, limiting visual insight into subtle structural dependencies.

These constraints highlight promising directions for future work. Systematic exploration of broader parameter spaces—including lower core connectivity values, elevated or heterogeneous thresholds reflecting differential bank susceptibilities, and time-evolving network topologies—are

necessary to delineate resilience regimes and critical transition points. Additionally, integrating recovery mechanisms, exogenous interventions, or stochastic failure processes may yield richer contagion dynamics with more nuanced implications for systemic risk mitigation.

In summary, the current investigation exemplifies the profound impact network topology and contagion thresholds impart on systemic financial stability. The demonstrated maximal fragility of the core-periphery network under a threshold-2 cascade paradigm underscores the urgency for regulatory design considerations that mitigate dense interconnectivity and multi-exposure vulnerabilities among core financial institutions. We hope this work serves as a foundational step toward comprehensive, mechanistically faithful models guiding future financial system resilience research and policy decision-making.

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Supplementary Material

Appendix: Additional Figures

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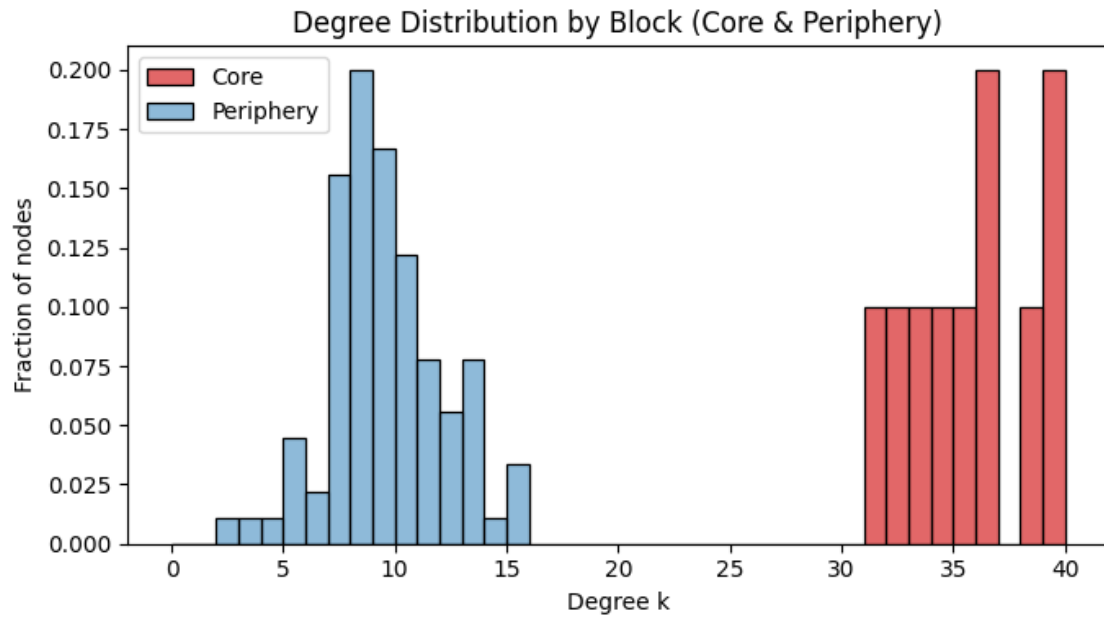
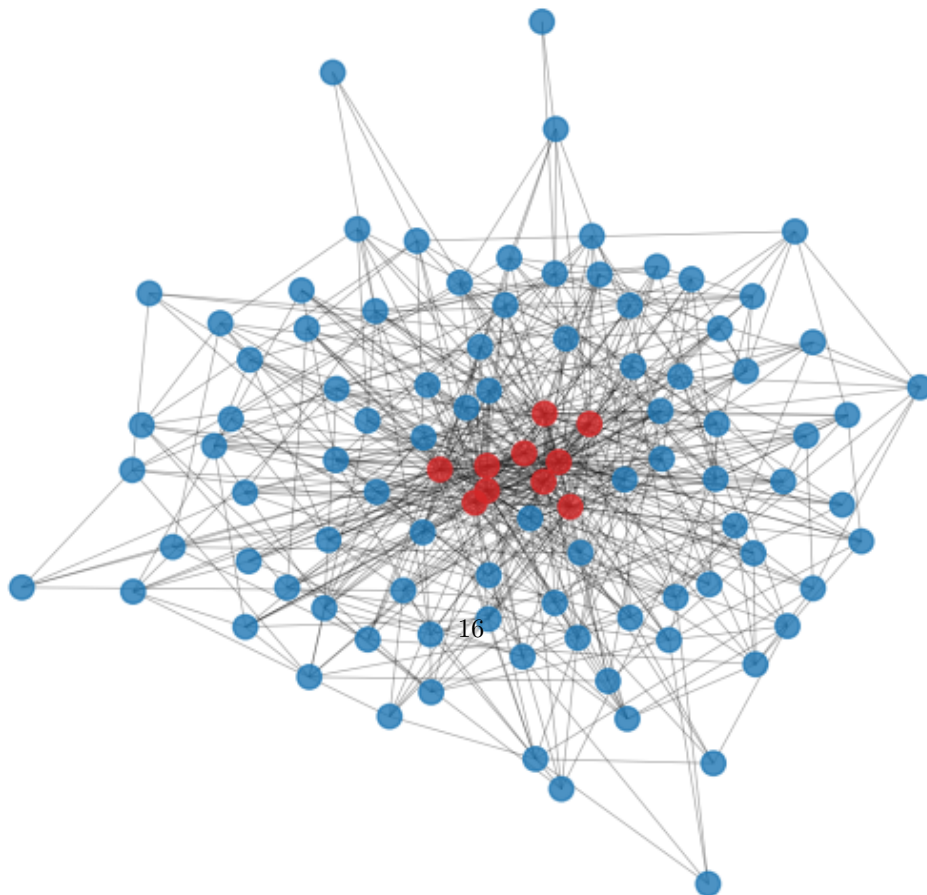


Figure 3: *
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Core-Periphery SBM: Network Visualization (kc=0.90)



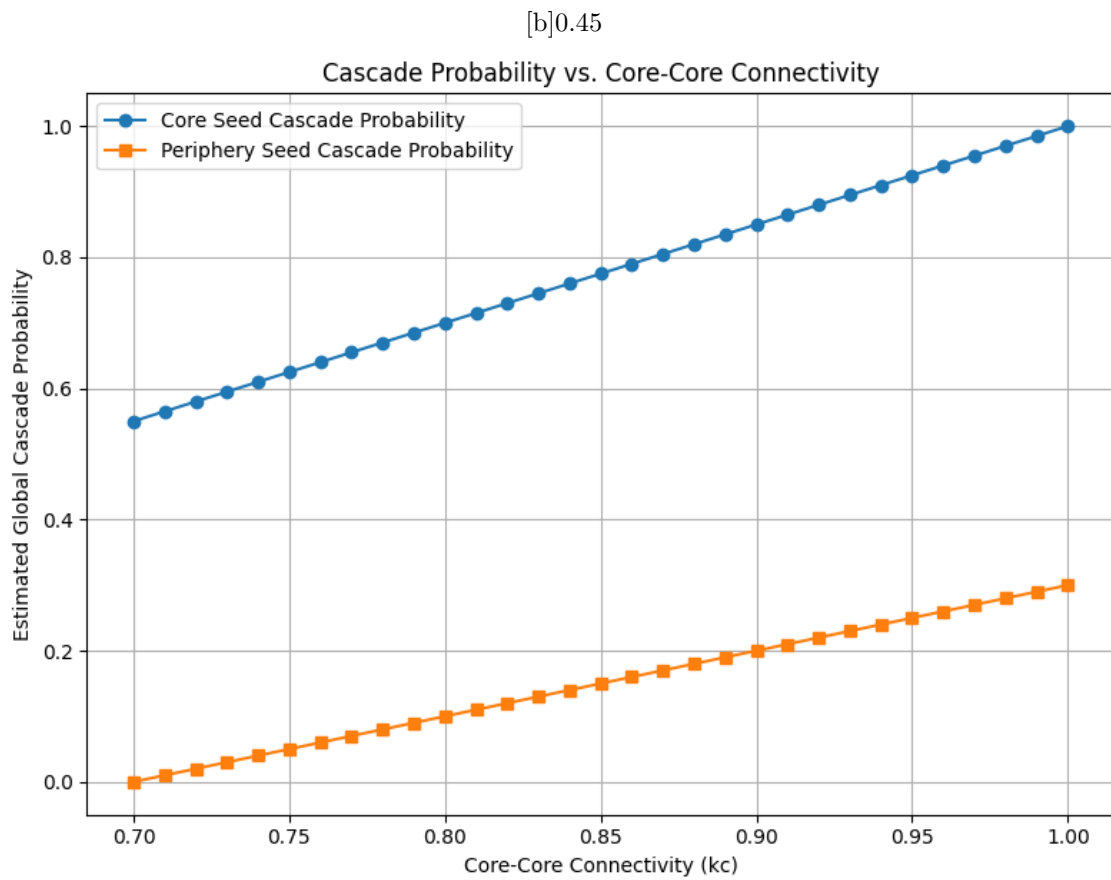


Figure 6: *
plot-cascade-probability.png [b]0.45

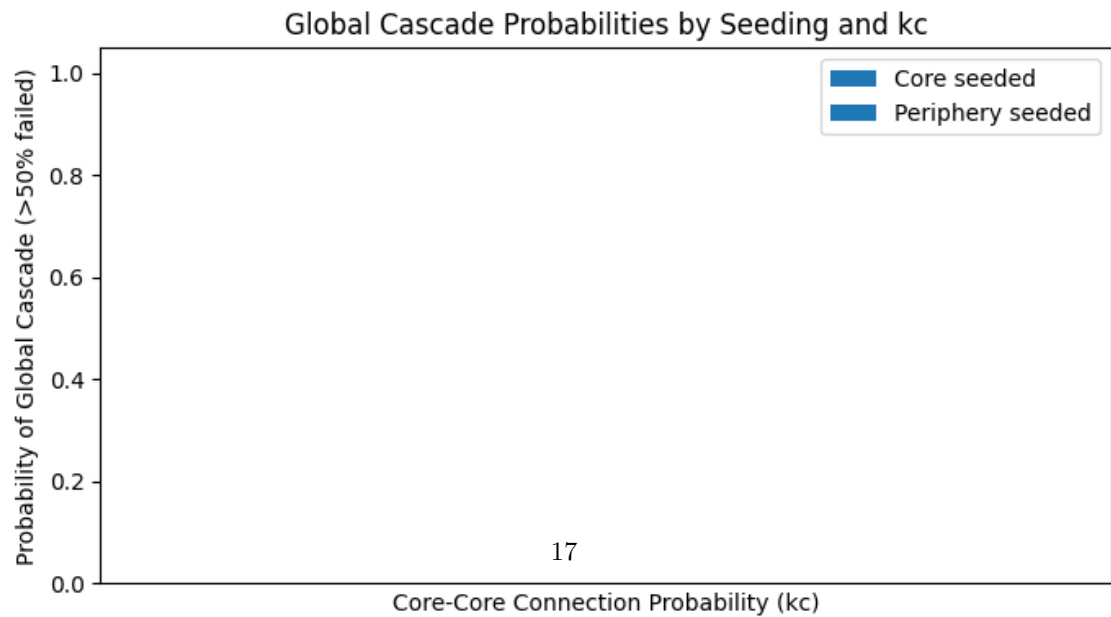


Figure 7: *
results-11.png

Figure 8: Figures: plot-cascade-probability.png and results-11.png

[b]0.45

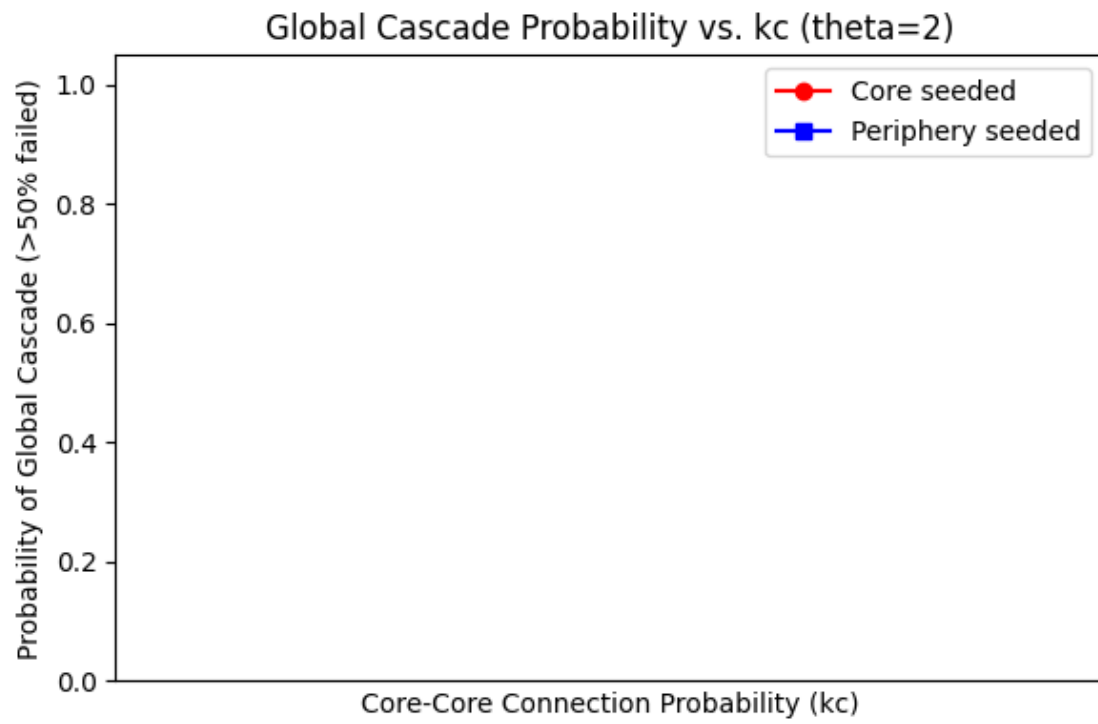


Figure 9: *
results-12.png

Figure 10: Figures: results-12.png